Behavioral Responses towards Risk Mitigation: An Experiment with Wild Fire Risks

by

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ABSTRACT. What are the behavioral effects of voluntary self-protection in situations where the probabilities are unknown to the agent? Virtually all naturally occurring environments of risk management involve subjective probabilities, and many allow decision makers to voluntarily mitigate risk using self-protection activities. To examine this environment we design a laboratory experiment in which incomplete information about probabilities is generated in a naturalistic way from the perspective of decision makers, but where the experimenter has complete information. Specifically, we use virtual simulations of property that is at risk of destruction from simulated wild fires. Using direct belief elicitation mechanisms we find that subjective beliefs over high and low risk scenarios underestimate the shift. Thus, predictions of voluntary self-protection activities based on such data would estimate a suboptimal willingness to invest. However, when offering subjects' self-protection opportunities, their choices indicate that they over-estimate the risk reducing effects and would in fact be willing to pay more than if they knew the objective probabilities. These findings have direct implications for the normative evaluation of risk management policies when risk perception is subjective.

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Most interesting choices in risky environments allow individuals to undertake self-protection actions that alter the risk that they face. In the business world this is one component of what is called risk management. Using the formal metaphor of economics, individuals choose the probabilities that apply to each outcome in a risky prospect, rather than just choosing between risky prospects with given probabilities. Consider the case of the risk that a wild fire, caused by a lightning strike, burns down your house. The likelihood of a lightning strike is exogenous, thus a homeowner cannot affect this event. However, this likelihood does not translate directly into an exogenous probability of damage to the house, since the homeowner can take various actions to mitigate that risk, such as removing dead wood and debris in the surrounding landscape.

Importantly, in almost all cases of voluntary risk management the risk is not precisely known. In such circumstances, an important determinant of the willingness to undertake risk mitigation is the subjectively perceived probability of damage. Manski (2004) argues convincingly against the rational expectations assumption, thus supporting the need for eliciting subjective beliefs. However, subjective beliefs inferred from standard direct elicitation mechanisms, such as scoring rules or betting mechanisms, may not represent subjective beliefs over effects of self-protection actions, if agents incorrectly perceive the effect these actions have on the risk. There are several reasons to suspect that this may be the case. First, a large literature in both psychology and economics now claims that choices and values are influenced by how the problems are framed (Tversky and Kahneman (1981)). Second, experiments in market-entry decisions show that subjects overestimate their ability to make profits post-entry, leading to suboptimal entry-decisions (Camerer and Cavallo (1999)).

Experiments using virtual reality (VR) provide an ideal study environment in which the probability can be known to the researcher but unknown to the decision maker. It is also an environment that incorporates many natural cues about the risk and is closer to field decision environments than are stylized tasks with information given as text and numbers. We ask whether the subjective beliefs differ based on whether they are directly elicited using betting instruments, or inferred from self-protection actions. If not, then one cannot use beliefs elicited over exogenously given risk to predict self-protection choices.

We compare two methods of eliciting subjective beliefs. One method is a betting mechanism over given but unknown probabilities. This is a direct elicitation method, like the stated beliefs approaches proposed by Manski (2004), but with response incentives that remove any hypothetical response biases.[1] The other method is an indirect elicitation method where subjective probabilities are inferred from action choices. Here the subject has the option to mitigate the risk through self-protection, and therefore to change the unknown probabilities by expressing a willingness to pay. In the risk mitigation treatment we give subjects the costly option of managing the forest using prescribed burns, thereby decreasing, but not eliminating, the amount of wild fire fuel and the risk of high cost fires. This choice is discrete: either implement a certain level of prescribed burn or not. This is a natural choice structure when using a prescribed burn as the fire management tool since there is rarely a choice of how much of the fuel to burn, but only the choice to burn it all or not. The subject owns a virtual house in the virtual forest, and we model salient incentives by giving the house a monetary value that will be paid out to the subject at the end of the experiment if the house has not burned.

Whether one uses direct or indirect elicitation methods, the tasks facing the subjects are risky and it is therefore necessary to also control for risk attitudes. We do so by presenting

[1] Hypothetical biases have been demonstrated both in valuation tasks (Cummings, Harrison, and Rutström (1995)) and in risky choice tasks (Holt and Laury (2002)), and there is no reason to expect that belief questions suffer less from hypothetical bias than any other questions.

subjects with a set of standard binary lottery choices commonly used to elicit risk attitudes. One might be tempted to estimate both beliefs and risk attitudes from the same task, however, as argued by Manski (2004), identification of both preferences and expectations is easier when using separate tasks since choice tasks alone may not have enough information.

Controlling for risk attitudes, we find that our subjects drastically overestimate loss probabilities in both elicitation mechanisms. However, the two mechanisms generate different relationships between the low and the high risk probabilities. In the direct elicitation mechanism, where the risk is exogenous, subjects underestimate the difference in loss probabilities. In the indirect elicitation mechanism where subjects make self-protection choices, they overestimate the reduction in the loss probability that the protection will lead to. Thus, if we want to predict how much would be voluntarily invested in risk mitigation based on the elicited subjective probabilities, the manner in which we elicit these probabilities matters. The finding that subjects overestimate the risk reduction that results from their mitigating investment resembles experimental findings of overconfidence in market entry experiments (Camerer and Cavallo (1999)). In these experiments, subjects overestimate their ability to make profits post-entry, and entry decisions are therefore suboptimal.

In the next section we briefly review the theory of self-protection and review two earlier experimental studies. We then describe our experimental design, our econometric strategy, and then give a detailed account of our estimation results.

I. Theory

Suppose there are two states of nature: for example, your house burns or it does not. We review here the expected utility theory of risk mitigation from Ehrlich and Becker (1972), hereafter EB. Let the probability of damage be p. Then the expected utility of an individual when no mitigation is possible is given by:

(1) $EU = (1-p)U(x) + pU(x-l)$

where *x* is initial wealth, and *l* is the loss experienced if the house burns. *Self-protection* is investment made to reduce the probability of incurring any damages when the bad outcome occurs. Let

(2) $P = P(p, d)$

be the effective risk mitigation function that takes into account the ability of the individual to change the risk faced, and where *p* is the exogenous risk of damage occurring, *d* is the amount of self-protection, and $P'(d) < 0$. The agent's problem is then to choose self-protection investment *d* to maximize:

(3) $EU = \big(1 - P(p,d)\big)U(x-d) + P(p,d)U(x-l-d)$

where l is the dollar damage caused. Alternatively, if *d* is discrete, the agent would compare EU with and without self-protection:

Shogren (1990) compares valuations across two risk mitigation mechanisms: self-protection and self-insurance, when the probabilities are known to the experimental participants. Shogren (1990) focuses on the asymmetry in the parametric changes of the choice environment that is produced by self-protection vs. self-insurance. Self-protection is modeled such that the probability of a loss is reduced to zero, leading instead to an increase in the probability of a gain to full certainty. Self-insurance, on the other hand, leaves the probabilities over gains and losses intact but reduces the monetary loss to zero. He finds that participants value self-protection higher than insurance, in line with the EU prediction. In a similar vein, Bruner (2009) tests the EU prediction that risk averse agents prefer a change in probability distributions to a change in the payoffs for equivalent increases in Expected Value, and finds that results support the EU prediction.

Both of these evaluations of self-protection vs. self-insurance under EU relied on agents knowing the objective probabilities. Thus, responses are only a function of the properties of the utility function. However, in most cases it is not reasonable to assume that agents have this knowledge, in which case they base their decisions on subjective, rather than objective, probabilities. This introduces the possibility that there are other sources of behavioral differences across choice frames than responses to asymmetries in utility. This is our focus. We ask if the elicited *subjective* probabilities differ across frames where choice options are defined over variations in payoffs only, as they are in betting mechanisms, or where choice options are defined over variations in subjective probabilities, as they are in choices over self-protection options.

We amend the theory presented above to reflect possible imprecisions in the mappings between subjective and objective probabilities we add a function that maps subjective probabilities to the experiences and information that agents use to form their beliefs:

(4) $\pi = f(p, e, I)$,

where π is the perceived, subjective probability, assumed to be a function of the objective probability p , experiences e, and information I. We would then have the risk mitigation function

(5) $\Pi = \Pi(\pi, d)$.

In our VR simulations we allow subjects to gain experiences so that they may form perceived probabilities, π . We elicit beliefs from betting mechanisms and self-protection tasks from the same subjects, ensuring that the VR experiences are the same for these tasks. However, we hypothesize that the framing of the choice tasks will affect the beliefs that subjects employ in the tasks. We hypothesize that either π or Π, or both, are affected by the frame. In particular, following the behavioral pattern observed in market entry games (Camerer and Cavallo (1999)), we expect $\Pi_d > P_d$, such that subjects over-estimate the effects of self-protection on resulting probabilities.

II. Experimental Design

The experimental design is built on a naturalistic presentation of the risk of damages, where VR simulations are used to mimic natural risk, but where no precise, numeric information of probabilities is given to subjects. VR provides a methodologically important intermediate environment between field experiments and lab experiments. The natural cues of field experiments are mimicked through simulated naturalistic cues in the VR environment, while still allowing the rigorous controls of a lab experiment. Our VR simulation is of wild fires in the Ashley National Forest in Utah, where the subject is the owner of a log cabin that gives him a monetary payout if it does not burn. The design includes a number of tasks that allow identification of the factors that theoretically influence decisions, including risk attitudes and probability perceptions. These tasks include two betting tasks (one for each a high and a low risk), three willingness to pay (WTP) tasks (as payments for self-protection, which lowers the risk from a high to a low one), a standard lottery task in the gain domain, and a standard lottery task in the loss domain.

Each of the 7 tasks involves a series of binary choices.[2] Every subject participates in all tasks, and one task is randomly selected at the end of the experiment to determine the subjects'

[2] Subjects were given 11 tasks, but only 7 are analyzed here. The additional 4 tasks were given after these 7 and should therefore not have influenced these choices.

earnings, following common experimental practice.[3] This has the advantage of avoiding any "wealth or portfolio effect" that may arise if subjects are paid for multiple decisions made at the same time.

The betting tasks and the WTP tasks use VR simulations of wild fires, and are used to elicit subjective probabilities with and without self-protection. These tasks constitute the core of the experiment, where subjects do not know the exact probabilities over events. Instead, each outcome is generated by running simulations with a set of parameters that determine the intensity, speed and direction of spread of a wild fire. These parameters are stochastic with known, discrete distributions. The effects that various combinations of these factors have on the wild fire are not known to the subjects, but they are given some limited exposure to that relationship before making their choices. This mimics the limited information conditions that are common in field decision situations.

A considerable amount of time in the experiment is spent on the instructions for the VR tasks, including an extensive explanation of the betting mechanism. We control for order effects by varying whether subjects experience the VR betting task first, followed by the VR WTP task, or *vice versa*. Following the VR tasks, subjects are also given a series of lottery tasks with known probabilities, intended to elicit risk attitudes.

The next section describes in detail the VR tasks used to elicit subjective beliefs. We explain both the betting mechanism and the WTP task. We then explain two lottery tasks with

[3] A simple procedure is used to ensure that the random nature of this process is credible, using the following instructions: "The box in front of you has 11 envelopes and 11 cards numbered 1 through 11. Please put one card into each envelope and close the envelopes. I will now shuffle these envelopes. The envelopes have now been carefully shuffled and I ask that you pick one of them. The number on the card in the envelope you selected determines which task you will be paid for. But you will not know which one until the end of the experiment when you will be allowed to open the envelope." All experiments were conducted with one subject at a time.

known probabilities. These vary in terms of the use of gain and loss frames, although the corresponding choices produce identical monetary outcomes.

The Virtual Reality Simulations

Subjects are told that the VR simulations are based on the Ashley National Forest in Utah, and that they have a virtual property in this area in the form of a log cabin. The path of the simulated fire spread is generated using FARSITE, a fire behavior simulation model developed by Finney (1998) and widely used by fire management professionals. The rendering software that performs the visual simulation of the forest and the fire is from Fiore, Harrison, Hughes and Rutström (2009). The simulated area is subject to wild fire, and in the WTP task subjects must make a decision whether to pay for a prescribed burn or not, which would reduce the risk that their property would burn. The prescribed burn option is discrete: either the entire forest is subject to a prescribed burn, and all excess fuel removed, or not. There is no option to do partial burns. There are no VR simulations of the prescribed burn itself. The prescribed burn merely causes the wild fire risk to change from high to low.

Subjects receive 3 pieces of information about the risk to their property. First, they are told that the background uncertainties are generated by (a) temperature and humidity, (b) fuel moisture, (c) wind speed, (d) duration of the fire, and (e) the location of the ignition point. They are also told that these uncertainties are binary for all but the last, which is ternary; hence there are 48 background scenarios. They are also told what the specific values are for these conditions (e.g., low wind speed is 1 mph, and high wind speed is 5 mph). Thus subjects could use this information, their own sense of how these factors play into wild fire severity, and their experiences and inferences from the VR experience explained below, to form some probability judgments about the risk to their property. The objective is to provide information in a natural manner, akin to what would be experienced in the actual policy-relevant setting, even if that information does not directly "tell" the subject the probabilities.

Second, the subject is shown some histograms displaying the distribution of acreage in Ashley National Forest that is burnt across the 48 scenarios. Figure 1 shows the histograms presented to subjects. The vertical axis is deliberately scaled in terms of natural frequencies defined over the 48 possible outcomes, and the scaling of the axes of the two histograms is identical to aid comparability. The qualitative effect of the enhanced prescribed burn policy is clear: to reduce the risk of severe wild fires. Of course, the information here is about the risk of the entire area burning, and not the risk of their personal property burning, and that is pointed out in the instructions.

Third, subjects are allowed to experience several of these scenarios in a VR environment that renders the landscape and fire as naturally as possible. Figure 2 illustrates the type of graphical rendering provided, although static images such as these do not do justice to the VR "presence" that was provided. Some initial training in navigating in the environment is provided, which for this software is essentially the same as in any so-called "first person shooter" video game.[4] The mouse is used to change perspective and certain keys are designated for forward, backward, and sideward movements, as well as up and down. The subject is then presented with the 4 practice scenarios and is then free to explore the environment, the path of the fire, and the fate of their property during each of these. Apart from the ability to move across space, subjects also have the option of moving back or forth in time within each fire scenario.[5]

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[4] For student subjects this interface is second nature.

[5] This points to another feature of the VR environment in settings where current action, or inaction, can lead to latent effects well into the future. The VR simulation interface can be used by subjects to "fast forward" and better comprehend those effects.

With this approach, subjects are able to form their own beliefs about the probability of damage. Contrary to decisions involving actual lottery tickets in most laboratory experiments, this risky environment has outcomes and probability distributions that are not completely known to the agent. We therefore expect the choices to be affected by individual differences not just in risk preferences but also in risk perceptions. We are particularly interested in the perception of risk that subjects form in this VR experiment, since this drives decisions on risk mitigation. Hence the instructions are designed to convey information about this risk as accurately as possible without explicitly giving numeric probabilities.

The instructions start with a brief introduction about the threats of wild fires and of prescribed burning as a fire management tool that can reduce the frequency and severity of fires. The idea of VR computer simulations is introduced, followed by instructions that explain the first experimental task, which is either the betting task or the WTP choice task. We vary the order of these 2 tasks across subjects. This is followed by a discussion of how the 5 background factors in the simulation affect the risk of damages to their property. We use dice to select background factors for each simulation, so that the likelihood of these selections is known, even though the effects they have on the risk to property are not. Subjects are made familiar with the idea that fires and fire damages are stochastic, and can be described through frequency distributions. They are shown the frequency distributions of the forest acreage burnt under all possible combinations of background factors as generated by the simulation program. They are not, however, shown frequency distributions of damage to their own property. The subjects then experience 4 dynamic VR simulations of specific wild fires, 2 for each of the cases with and without previous prescribed burns, rendered from the information supplied by FARSITE simulations that vary weather and fuel conditions. We selected these simulations to represent the most benign and the most intensive combination of factors for fire spread, and the subjects are told this. They are allowed to experience these simulations in any way they like. They may move around the landscape however they want, and they may move back and forth in time freely.

After having had the opportunity to form beliefs about the likelihood of the property burning in a fire, subjects are presented with the choice tasks. When all choice tasks are completed, one is selected randomly for payment. If the selected task involves a VR simulation, then as part of determining earnings a final simulation is run, using randomly selected background factors. These random selections are performed using dice. Whether or not the property burns in this final simulation impacts the earnings in the task.

We first describe the betting and WTP tasks where payments depend on outcomes of the VR simulations. Thereafter we describe the binary lottery tasks that do not use VR simulations, but instead use objective probabilities implemented using dice and are used to identify the risk attitudes of the subjects.

The Betting Tasks

The objective of the betting task is to directly recover the subject's belief that event A will occur instead of event B. Event A is when the property burns and event B is when it does not, so the two events are mutually exclusive. Assume that the subject is risk neutral and has no stake in whether A or B occurs other than the bets being made on the event. There are 9 bookies, each willing to take a bet at stated odds. Table 1 shows odds for the two events in the form that they are naturally stated in the field: what is the amount that the subject would get for a $5 bet if the indicated event occurred? Each row in Table 1 corresponds to a different bookie with different odds.

In our design the subject is simply asked to decide how they want to bet with each of the 9 bookies, understanding that only one of these bookies may be the one selected for payment at the end of the experiment. Their "switch point," over the 9 bookies, is then used to infer their subjective belief. The basic experimental design and estimation strategy are borrowed from Andersen, Fountain, Harrison, Hole and Rutström (2012).[6]

Consider a subject that has a personal belief that A will occur with probability 0.75, and assume that the subject *has* to place a bet with each bookie, knowing that only one of these bookies will actually be played out. The (risk neutral) subject would rationally bet on A for every bookie offering odds that corresponded to a lower probability than 0.75 of A winning, and then switch over to bet on B for every bookie offering odds that corresponded to a higher probability than 0.75 of A winning. These bets are shown in Table 1, and imply gross earnings of \$50 or \$0 with the first bookie, \$25.00 or \$0 with the second bookie, and so on. The expected gross earnings from each bookie can then be calculated using the subjective belief of 0.75 that the subject holds. Hence the expected gross earnings from the first bookie are (0.75 × \$50) + (0.25 × \$0) = \$37.50, and so on for the other bookies. A risk neutral subject with the subjective probability 0.75 would bet on event A for the first 7 bookies and then switch to event B.

Each subject faces two betting tasks in our experiment. The first task is for the event that the house burns when the fuel load is high (or a prescribed burn is not used); and the second task is for the event that the house burns when fuel level is low (or a prescribed burn is used). Thus, the objective probability in the first task is higher than in the second. The subject is given a

[6] Familiar scoring rule procedures are formally identical, since each probability report implicitly generates a bookie willing to bet at certain odds. Thus when the subject makes a report in a Quadratic Scoring Rule, for example, the subject is in effect choosing to place a bet on the event occurring with payoffs given by odds that are defined by the scoring rule. By making one report instead of another, the subject is then choosing one bet over another, or equivalently, in our design, one bookie over another.

fictional $5 stake to bet with in each of the 2 betting tasks, and a bet has to be placed for each of the 9 bookies. The stakes are fictional in that the subject cannot choose not to bet. Furthermore, the $5 for one bookie is not transferable to other bookies, and one of the bets will be selected at random to be actually played out.

If a betting task is selected to be played out, then a final simulation would be run to determine the earnings. This simulation would either have a high or a low fuel load, depending on which betting task is selected. All other background factors are randomly selected. In the betting tasks the subjects cannot affect the probabilities that the house will burn. These tasks therefore do not offer self-protection options.

The WTP Tasks

The design of the WTP choice task offers subjects self-protection options. Earnings to subjects depend on an initial endowment of money, the monetary value of their property, and whether or not the property burns. The subjects have the option to use some or all of their initial money endowment to pay for a prescribed burn. Recall that the amount of prescribed burn, or the amount of removed fuel, is given, so the choice is either to prescribe burn all of the forest or to do nothing. After having viewed the 4 simulations from which they form their subjective beliefs, subjects are shown a list of prices that can be charged for a prescribed burn. Table 2 shows this list for one of the three WTP tasks. In this task the property is worth $8 if it survives the fire, and the initial money endowment is $20. The first row shows the case where self-protection is free: the price of prescribed burn is $0. For each row below that, the cost of a prescribed burn increases by $2 until a maximum price of $8 is reached. On each row the subject will choose either "Yes," for agreeing to pay the price and have a prescribed burn done, or "No," for preferring to keep the money and not having a prescribed burn. Only one row could potentially be selected for payment.

There are three such WTP tasks that differ by how much the house is worth and the level of the initial endowment. In addition to the task with a house valued at $8 and an initial endowment of $20, there is a task where the house is valued at $28 with an initial endowment of $60, and a task where the house is valued at $38 with an initial endowment of $80. Using these multiple tasks allows us to identify both the probability of the high risk case and the probability of the low risk case. The choice data generated in these 3 tasks can be analyzed as data from a series of pairwise options, but using subjective probabilities since the objective probabilities are not known to subjects. Whether or not one uses the betting task data or the WTP task data to infer probabilities, it is important to control for risk attitudes. We use additional choice tasks that present subjects with risky options with known probabilities to infer risk attitudes.

Choice Tasks with Known Probabilities

We present subjects with two pairwise choice tasks where the probabilities are precisely known and no VR simulation is used. All of these choice tasks use ordered lists of pairs of lotteries, which we call lotteries S or R. The letter S (R) refers to the relatively safer (riskier) of the two lotteries. Table 3 illustrates the basic payoff matrix presented to subjects in the first such task, which we will refer to as the standard lottery task. The first row of Table 3 shows a choice between getting $24 for certain (lottery S) or $1 for certain (lottery R). The second row shows a more interesting choice, where lottery S offers a 90% chance of receiving $24 and a 10% chance of receiving $26. The expected value of this lottery is shown as $24.20, although the EV columns are not presented to subjects. Similarly, lottery R in the second row has prizes $50 and

$1, for an expected value of $5.90. Thus the two lotteries have a difference in expected value of $18.30. As one proceeds down Table 3, the expected value of both lotteries increases, but the expected value of lottery R becomes greater relative to the expected value of lottery S.

Each subject chooses S or R for each row, and only one row may later be selected at random for payment. The logic behind this test for risk aversion is that only risk loving subjects would take lottery R in the second row, and only very risk averse subjects would take lottery S in the last row. Arguably, the first row is simply a test that the subject understood the instructions, and has no relevance for risk aversion at all. A risk neutral subject should switch from choosing S to R when the EV of each is about the same, so a risk neutral subject would choose S for the first five rows and R thereafter. In each row the subject is equally likely to get the bigger prize or the smaller prize, which rules out the possibility of self-protection; the only difference is the payoff amount.

The second choice task using known probabilities presents the subjects with the same pairwise lottery choices as in the standard lottery task, but now they are framed as losses instead of gains. For example, instead of winning $26 the subject now loses $24 from an initial endowment of $50, with probabilities applied as before. Accordingly, for an endowment of $50 our prizes after "reflections" into a loss framing become -$24, -$26, -$0 and -$49.[7] The basic hypothesis to be tested is that the risk aversion coefficients in the gain and loss frames are identical. This task is illustrated in Table 4.

Our primary interest in restating the standard lottery task in the loss frame is to make it comparable with the framing of other tasks in our experiment. Both the betting tasks and the

[7] Holt and Laury (2008) undertook a similar exercise but where subjects earned their initial endowment in earlier experimental tasks, which averaged $43 and ranged from $21.68 to $92.08. They find evidence of risk averse behavior in the gain domain and risk loving behavior in the loss domain.

WTP tasks are stated as losses from initial endowments, mimicking how fires in the naturally occurring field imply losses from some initial property endowment. The lotteries in the gain and loss frame are, however, identical only to the extent that the assumption about the reference point being a $0 prize in the lottery is valid. As emphasized in Harrison and Rutström (2008; p.95ff.), it is difficult to determine the reference point that the subject actually uses in tasks such as these. It is possible, for instance, that the subject has a reference point of $50, such that he views all of the net prizes in the loss frame lottery as positive and therefore perceives no losses. The expected values of the lotteries with $0 and $50 reference points are the same. Hence in either case a risk neutral subject chooses lottery S for the first five rows and lottery R for the last five rows.[8]

Allowing for loss aversion, it is possible that subjects make different choices in the lotteries presented in Tables 3 and 4 if they perceive a reference point of $0. We test whether estimated risk aversion coefficients in the gain and loss domains are identical and whether there is evidence of such a framing effect.

III. Results

We have two kinds of tasks: lottery tasks with known objective probabilities and VR tasks with probabilities unknown to the subject. We can infer risk attitudes from the observations on choices in the lottery tasks. We can then infer subjective probabilities from the observations on choices in the betting and WTP tasks that rely on VR simulations as providing information about risk. The sample consists of 57 subjects recruited from the student population of the University of Central Florida.

[8] Of course, $0 and $50 are not the only two possible reference points. If the subject integrates the show up fee of $5 into his wealth coefficient, then the reference points are $5 and $55 respectively. If he integrates his lifetime income or income outside the current experiment things get more complicated. Inferences about lotteries in the loss domain are very sensitive to assumptions about the reference point.

Estimating Risk Attitude under Expected Utility Theory (EUT)

We assume that utility is defined by the Constant Relative Risk Aversion (CRRA) function

(5) $U(x) = \lambda x^{1-r}/(1-r)$

where x is the lottery prize and $r \neq 1$ is a parameter to be estimated. Thus r is the CRRA coefficient, where $r = 0$ corresponds to risk neutrality, $r < 0$ to risk loving, and $r > 0$ to risk aversion. The parameter λ captures a possible reflection effect when the lottery outcome is framed as a loss, and is set equal to 1 in the gain frame. The variable x in the estimation is then the net payoff, i.e. the initial endowment minus the loss.[9] All lotteries used in our experiment have two outcomes. If the probability of the worse outcome is p, expected utility (EU) is simply the probability weighted utility of each outcome in each lottery i,

(6) $EU_i = (1-p)U\left(x_i^g\right) + pU\left(x_i^b\right)$

where the superscript g on the lottery prize x indicates the good outcome and the subscript b indicates the bad outcomes.

The choice depends on the difference in EU between lottery S (safe) and R (risky):

$\Delta EU = EU_R - EU_S$

This latent index, based on latent preferences, is then linked to the observed choices using a standard cumulative normal distribution function $\Phi(\Delta EU)$.

The conditional log-likelihood function is then

$$\ln L(r; y.X) = \sum_i [(\ln \Phi(\Delta EU) \times I(y_i = 1)) + (\ln(1 - \Phi(\Delta EU)) \times I(y_i = -1))],$$

[9] Allowing more flexible functional forms that model possible income effects, such as the Expo-Power function of Saha (1993), does not affect our findings in any significant manner.

where $I(.)$ is the indicator function and $y_i = 1$(-1) indicates the choice of the R (S) lottery. The only variable that has to be estimated from this log-likelihood function is *r*.

An important extension of the core model is to allow subjects to make errors in the decision process. The notion of error is one that has already been encountered in the form of the statistical assumption that the probability of choosing a lottery is not 1 when the EU of that lottery exceeds the EU of the other lottery. This is implicitly assumed when one adopts a link function, of the kind shown in Figure 3, to go from the latent index to observed choices. The contextual error specification, suggested by Wilcox (2011), introduces a normalizing term ν for each lottery pair, and a structural "noise parameter" μ to allow for error from the deterministic EU model: $\nabla EU = [(EU_R - EU_S)/\nu]/\mu$.[10]

To allow for subject heterogeneity with respect to risk attitudes, the parameter *r* is modeled as a linear function of observed individual characteristics of the subject. For example, assume that we only had information on the age and sex of the subject, denoted **Age** (in years) and **Female** (0 for males, and 1 for females). Then we would estimate the coefficients α, β and η in $r = \alpha + \beta \times \text{age} + \eta \times \text{female}$. The covariates we use are all binary. The variable **Age** is given in years over 17; **Female** is a dummy for whether the subject is female or male; **Hispanic** is a dummy for Hispanic heritage; **Business** is whether or not the subject is a business major;

[10] The normalizing term ν is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair, and ensures that the *normalized* EU difference $(EU_R - EU_S)/\nu$ remains in the unit interval. This normalization allows one to define robust measures of "stochastic risk aversion," in parallel to the deterministic concepts from traditional theory. When $\mu = 1$ we return to the original specification without error. As μ increases, the above index falls until, at $\mu = \infty$, it collapses to zero, so that the probability of either choice becomes ½. In other words, as the noise in the data increases, the model has less and less predictive power until at the extreme the prediction collapses to 50:50 or equal likelihood of both choices.

GPAhigh is for subjects with a self-reported GPA higher than 3.24; **Works** is a dummy for whether or not the subject is employed.

In this design multiple responses are elicited from each subject. This may lead to clustering, or heteroskedasticity. Therefore while estimating the model it is essential to correct for clustering effects. We estimate this model on the data from all the lottery tasks with known probabilities: the standard lottery, the loss frame lottery and the four self-protection frame lotteries. These results are shown in Tables 5a, 5b and 5c.

We find evidence of modest risk aversion, with a CRRA coefficient of 0.33 as shown in Table 5a, consistent with a large body of existing literature reviewed by Harrison and Rutström (2008). None of the demographic variables we include is individually significant in Table 5b. Importantly, we do not find a framing effect of the task being presented in the loss frame, as shown in Table 5c. The coefficient for λ, which would indicate a reflection effect, is 1.12 and not significantly different from 1. Because of this result we can simplify our analysis by not including this parameter in our further analysis.

Jointly Estimating Belief and Risk Attitudes under SEUT

Subjective beliefs about the risk of property damage from fires can be inferred from both the betting tasks or from the WTP tasks. The beauty of using a controlled VR experiment is that, even though probabilities are not known to subjects, they are known to the experimenter. We control for the risk attitude of subjects by jointly estimating risk attitudes and beliefs, using data from all choice tasks for the same subject.

A subject that bets on the house burning (B) in the betting tasks receives the EU given by

$$EU\,|_{bet\ on\ B} = \pi_B \times U\text{ (payout if B occurs | bet on B)} + (1-\pi_B)\times U\text{ (payout if NB occurs | bet on B)}$$

, where NB refers to the event "the house does not burn," and π_B is the subjective probability that B will occur. We use the notation π for the subjective probability to distinguish it from *p*, the objective probability. The example in the second row of Table 1 now is evaluated as

$$EU\,|_{bet\ on\ B} = \pi_B \times (25)^{(1-r)}/(1-r) + (1-\pi_B) \times U(0)^{(1-r)}/(1-r)$$

and $EU\,|_{bet\ on\ NB} = \pi_B \times (0)^{(1-r)}/(1-r) + (1-\pi_B) \times (6.25)^{(1-r)}/(1-r)$.

The index function is again $\nabla EU = [(EU_{NB} – EU_B)/\nu]/\mu$. An increase in this index should increase the likelihood of betting on event NB rather than event B. Subjects have two betting tasks, one for the forest that has been prescribed burn (the safe case) and one for the forest that has not been prescribed burn (the risky case). Thus the probabilities, π_B, will not be the same for the two betting tasks, so we elicit both π_B^{risky} and π_B^{safe}.

In the WTP tasks π_B^{safe} is the subjective probability of the house burning down when prescribed burning is implemented, and π_B^{risky} is the subjective probability that the house will burn down if no prescribed burning is implemented. More generally, $EU_{safe} = \pi_B^{safe} \times U($payout net of cost of prescribed burn if B$) + (1-\pi_B^{safe}) \times U($payout net of cost of prescribed burn if NB$)$ and $EU_{risky} = \pi_B^{risky} \times U($payout if B$) + (1-\pi_B^{risky}) \times U($payout if NB$)$.

The latent index in this problem is the difference in EU from paying for prescribed burning and not paying for prescribed burning: $\Delta EU = [(EU_{risky} - EU_{safe})/\nu]/\mu$ An increase in this index should increase the likelihood of selecting the risky option, i.e. of not paying for prescribed burn. Apart from r, ν and μ, we now need to estimate the two subjective probabilities π^{safe} and π^{risky}. The *joint* maximum likelihood problem is to find the values of all of these parameters that best explain observed choices in the belief elicitation tasks, WTP tasks and lottery tasks.

Detailed maximum likelihood estimates are contained in Table 6. We estimate this model including observations on all 7 tasks. The lottery tasks with known probabilities serve the purpose of identifying risk attitudes, and we confirm that adding data from the betting and WTP tasks does not change the estimated risk attitude appreciably. The pooled estimate of *r* shown in Table 6 is 0.33, and is not affected by adding the VR tasks.

We find evidence that subjects overestimate the loss probabilities both for the safe and the risky case. In Table 6 the constant terms reflect the betting task, and the WTP terms are the equivalent estimates for the WTP task. The constant term for the perceived probability with prescribed burn, π_B^{safe}, is 0.40 instead of the objective value 0.06; and the perceived probability without prescribed burn, π_B^{risky}, is 0.56 instead of the objective value 0.29.

We define willingness to invest (WTI) as the amount of money that the subject is willing to invest in the risk reducing prescribed burn. Recall that the degree of risk reduction of the prescribed burn is not a choice. The choice is only over whether to apply the prescribed burn or not at various costs. These overestimations lead to higher predicted willingness to invest (WTI) than if the WTI has been based on objective probabilities, but only in the presence of self-protection options. We infer the WTI from the Certainty Equivalents (CE). Using the *objective probabilities* and the estimated risk attitudes we find a CE for the safe case of $19.48 and a CE for the risky case of $17.54. The difference between these CE is the WTI in the prescribed burn, which is $1.94, with a 95% confidence interval of [$1.90, $1.98]. If instead we calculate the CE based on the *subjective probabilities* from the betting tasks, which are much higher, we find an implied WTI of $1.27, with a 95% confidence interval of [$0.99, $1.55]. The overestimation of the safer probability, π_B^{safe}, thus has a stronger influence on the WTI than the overestimation of the riskier probability, π_B^{risky}, such that the implied WTI for prescribed burn is less than one would find based on the objective probabilities. The confidence intervals of the objectively and subjectively calculated WTI do not overlap, so this is a statistically significant shift. The exact dollar values appear small only because these calculations are based on the low house value of $8. For a house value of $28 one would instead find a WTI of $6.87 based on objective probabilities and $4.45 based on subjective probabilities.

When subjects are able to engage in self-protection, as in the *WTP tasks* shown by the WTP coefficient in Table 6, we find that the subjective probability for the risky case goes to 1.0, but the subjective probability for the safe case drops to 0.31. The CE when the house is valued at $8 is now $12.00 and $17.53, respectively for the high and low risk case, resulting in a much higher WTI of $5.53 with a 95% confidence interval of [$4.99, $6.08]. Again, this interval does not overlap with the objective interval or the interval without self-protection options, so the shift is statistically significant. When the house is valued at $28 the WTI for mitigation is $19.27. Figure 4 shows the distributions of the subjective probabilities from a model that includes our demographic variables. Not only do we see that the implied WTI is higher with self-protection than without self-protection, we also see that the inferred subjective probabilities are much more dispersed in the former case.

Thus, based on the betting task alone one may be tempted to conclude that voluntary risk mitigation would lead to underinvestment, but once subjects are allowed to self-protect they are in fact overinvesting in mitigation. Recall that the amount of mitigation in these tasks is constant, and the investments are only measures of how much subjects are willing to spend on this mitigation.

IV. Conclusion

Risk attitudes and subjective beliefs are two fundamental determinants of decision making under risk and risk management. In many field settings in which there is risk and uncertainty, agents have the ability to mitigate risk through some form of self-protection. When predicting how much voluntary self-protection will take place one can rely either on assumptions of rational expectations, direct elicitation of beliefs, or indirect elicitation of beliefs. Manski (2004) argues against rational expectations and in favor of direct elicitation. Our results provide evidence that direct elicitation does not generate measures of subjective beliefs that match those participants use when actually undertaking self-protection. Thus, if voluntary risk mitigation investments are predicted using directly elicited subjective probabilities they will dramatically underestimate the willingness to invest observed in actual self-protection decisions.

Table 1. Betting Task with Stake of $5

Bet on A and earn if…		*Bet on B* and earn if…		Gross expected value of betting when probability of A is 0.75		
A occurs	B occurs	A occurs	B occurs	A	B	Difference
$50.00	$0	$0	$5.55	$37.50	$1.39	$36.11
$25.00	$0	$0	$6.25	$18.75	$1.56	$17.19
$16.65	$0	$0	$7.15	$12.50	$1.79	$10.71
$12.50	$0	$0	$8.35	$9.38	$2.09	$7.29
$10.00	$0	$0	$10.00	$7.50	$2.50	$5.00
$8.35	$0	$0	$12.50	$6.26	$3.13	$3.13
$7.15	$0	$0	$16.65	$5.36	$4.16	$1.20
$6.25	$0	$0	$25.00	$4.69	$6.25	-$1.56
$5.55	$0	$0	$50.00	$4.16	$12.50	-$8.34

Table 2. Price List for WTP when House is Worth $8

Cost	Yes, I choose prescribed burn	No, I do not choose prescribed burn
$0	Yes	No
$2	Yes	No
$4	Yes	No
$6	Yes	No
$8	Yes	No

Table 3. Standard Lottery Task in Gain Domain

Lottery S				Lottery R				EV^S	EV^R	Difference
p($24)		p($26)		p($1)		p($50)				
1	$24	0	$26	1	$1	0	$50	$24.0	$1.0	$23.0
0.9	$24	0.1	$26	0.9	$1	0.1	$50	$24.2	$5.9	$18.3
0.8	$24	0.2	$26	0.8	$1	0.2	$50	$24.4	$10.8	$13.6
0.7	$24	0.3	$26	0.7	$1	0.3	$50	$24.6	$15.7	$8.9
0.6	$24	0.4	$26	0.6	$1	0.4	$50	$24.8	$20.6	$4.2
0.5	$24	0.5	$26	0.5	$1	0.5	$50	$25.0	$25.5	-$0.5
0.4	$24	0.6	$26	0.4	$1	0.6	$50	$25.2	$30.4	-$5.2
0.3	$24	0.7	$26	0.3	$1	0.7	$50	$25.4	$35.3	-$9.9
0.2	$24	0.8	$26	0.2	$1	0.8	$50	$25.6	$40.2	-$14.6
0.1	$24	0.9	$26	0.1	$1	0.9	$50	$25.8	$45.1	-$19.3

Table 4. Standard Lottery Task in the Loss Domain with Initial Endowment of $50

Lottery S				Lottery R						
p(-$26)		p(-$24)		p(-$49)		p(-$0)		EV^S	EV^R	Difference
1	-$26	0	-$24	1	-$49	0	-$0	-$26.0	-$49.0	$23.0
0.9	-$26	0.1	-$24	0.9	-$49	0.1	-$0	-$25.8	-$44.1	$18.3
0.8	-$26	0.2	-$24	0.8	-$49	0.2	-$0	-$25.6	-$39.2	$13.6
0.7	-$26	0.3	-$24	0.7	-$49	0.3	-$0	-$25.4	-$34.3	$8.9
0.6	-$26	0.4	-$24	0.6	-$49	0.4	-$0	-$25.2	-$29.4	$4.2
0.5	-$26	0.5	-$24	0.5	-$49	0.5	-$0	-$25.0	-$24.5	-$0.5
0.4	-$26	0.6	-$24	0.4	-$49	0.6	-$0	-$24.8	-$19.6	-$5.2
0.3	-$26	0.7	-$24	0.3	-$49	0.7	-$0	-$24.6	-$14.7	-$9.9
0.2	-$26	0.8	-$24	0.2	-$49	0.8	-$0	-$24.4	-$9.8	-$14.6
0.1	-$26	0.9	-$24	0.1	-$49	0.9	-$0	-$24.2	-$4.9	-$19.3

Table 5a. Estimated Risk Attitudes from Lottery Tasks

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.21	0.44
μ	Constant	3.41	0.67	0.00	2.11	4.71

† *p*-value=0.76 for test of coefficient value significantly different from 1

Table 5b. Maximum Likelihood Estimate of Risk Attitudes allowing for Demographic Effects

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.21	0.44
	Age	-0.00	0.02	0.91	-0.03	0.03
	Female	0.14	0.13	0.27	-0.11	0.39
	Hispanic	-0.05	0.17	0.79	-0.38	0.29
	Business	-0.01	0.12	0.92	-0.25	0.22
	GPAhigh	0.10	0.15	0.48	-0.18	0.39
	Works	-0.19	0.13	0.15	-0.44	0.06
μ	Constant	0.18	0.04	0.00	0.15	0.20

Table 5c. Maximum Likelihood Estimate of Risk Attitudes in the Loss Frame

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.34	0.07	0.00	0.21	0.47
λ	Constant	1.12	0.17	0.00 †	0.79	1.46
μ	Constant	0.19	0.02	0.00	0.14	0.24

† *p*-value=0.67 for test of coefficient value significantly different from 1

Table 6. Joint Estimate of Risk Attitude and Subjective Beliefs

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.22	0.44
π_B^{safe}	Constant	0.40	0.01	0.00	0.37	0.43
	WTP	0.31	0.04	0.00	0.23	0.39
π_B^{risky}	Constant	0.56	0.01	0.00	0.54	0.58
	WTP	1.00	†	†	†	†
μ	Constant	0.13	0.01	0.00	0.10	0.15
	WTP	0.25	0.05	0.00	0.14	0.35
	Risk	0.18	0.02	0.00	0.15	0.21

† When estimating the probability of the house burning in the risky scenario where the forest has not been treated with prescribed burn, the estimate is too close to the corner solution of 1.0 to give us a reliable standard error.

Figure 1. Histogram Displaying Distribution of Forest that Burned

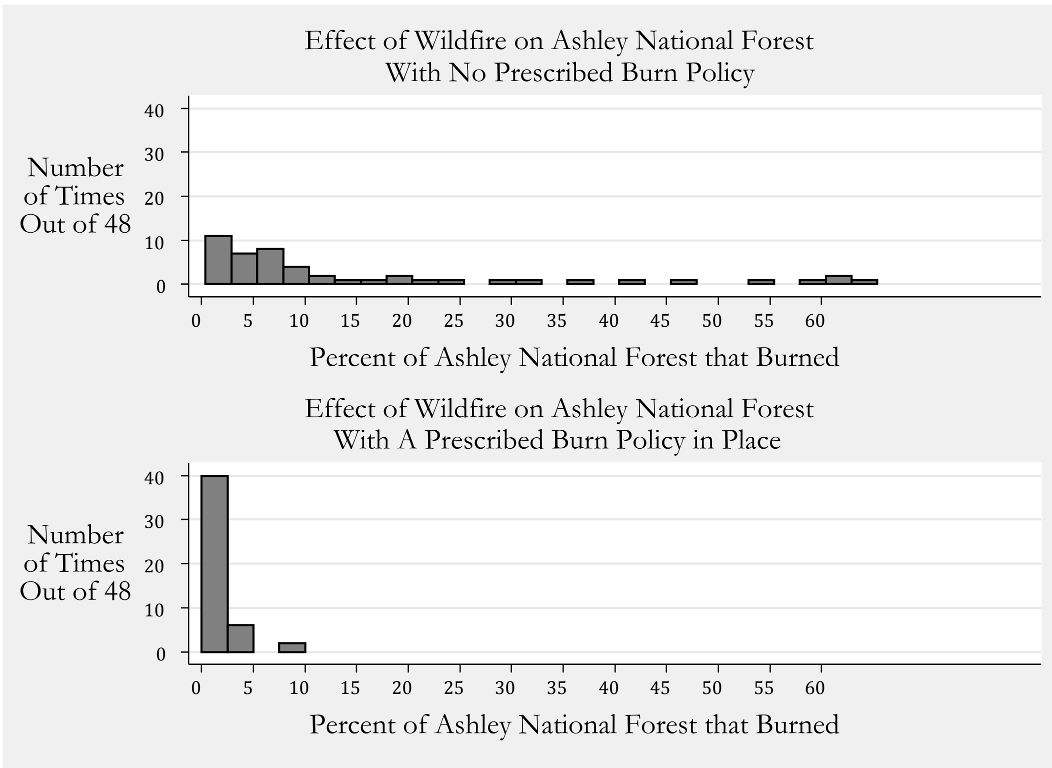


Figure 2. Illustrative Images from VR Interface

Figure 3. Normal and Logistic Cumulative Density Function

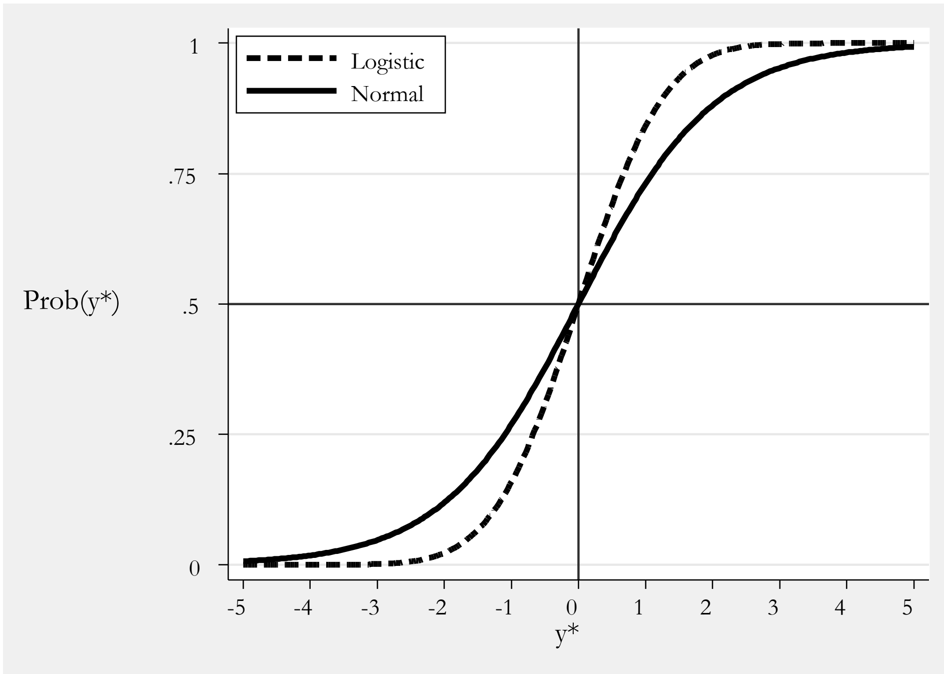
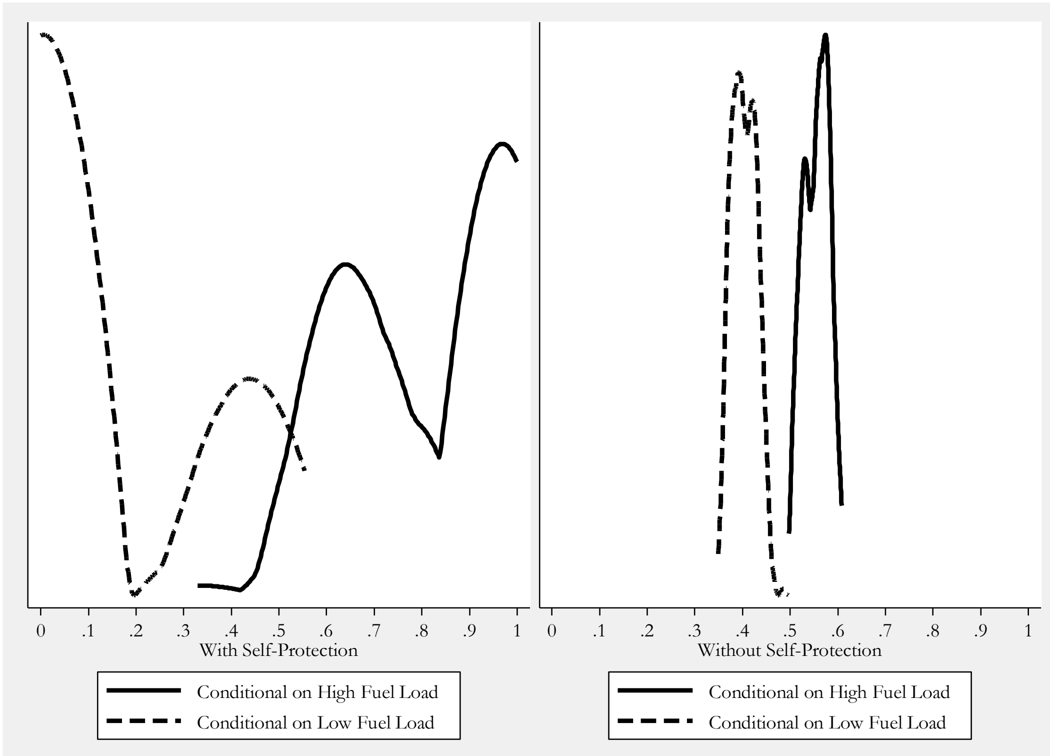


Figure 4. Estimated Subjective Probabilities of House Burning with and without Self-Protection



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Appendix A: Experiment Instructions (FOR ONLINE POSTING ONLY. NOT TO BE INCLUDED IN PUBLISHED PAPER)

[The instructions have been edited to take up less space. Page formatting differs from that used in the experiment]

Welcome to the experiment. Today you will perform several tasks. There are 11 tasks in total. For each task we will first describe the task to you and, after you have had a chance to ask questions, you will make your decision. At the end of the experiment you will be paid for one of these tasks.

Let me explain how we select the task to pay you. The box in front of you has 11 envelopes and 11 cards numbered 1 through 11. Please put one card into each envelope and close the envelopes. I will now shuffle these envelopes.

The envelopes have now been carefully shuffled, and would like you to pick one of them. The number on the card in the envelope you selected determines which task you will be paid for. You will not know what that number is until the end of the experiment, when you will be allowed to open the envelope.

In this part of the experiment you will make decisions about forest fires that pose a threat to homes, cars, boats, businesses, etc., and can cause millions of dollars of damage. For example, the total economic cost estimated for the 1998 wild fires in Florida was at least $448 million.

A build-up of wild fire fuel in the form of brush, dead branches, logs and pine needles on the forest floor has occurred over several decades. As a result, when wild fires are ignited they spread faster and burn longer than would otherwise be the case. During drought years the fuel moisture levels are low and compound the risks. In addition, when winds are strong the spread is faster and the damages more extensive.

Prescribed burning has been used to prevent wild fires from becoming intensive and spreading quickly. Prescribed burning involves having fire professionals periodically set fires to clear the forest floor of the excess brush, dead branches and pine needles. These prescribed fires are easier to manage than wild fires since prescribed fires do not burn as intensely and they can be directed away from housing structures. The effect of using prescribed burning is to lower the fuel load in the forest so if a fire starts it will be less intensive and spread more slowly.

Several computerized simulation programs have been developed in order to predict the spread and severity of wild fires with high accuracy. They are used by fire fighters during actual wild fires to predict the spread of fire and the best actions to contain the fire and minimize damage. These simulations are based on the landscape and urban settlements in specific regions of the US and therefore provide good examples of potential fire risks. We are going to use one such simulation program in this section, developed by the United States Forest Service.

The forest area that we are simulating is based on the topography and vegetation of Ashley National Forest in Utah. We are going to let you run through several simulations so you can experience the effect of wild fires with and without a prescribed burn program. The difference between the simulations with and without a prescribed burn is entirely due to differences in the fuel load of the forests. The fuel load with the prescribed burn is much lower. We also vary other factors that affect the severity of the fires, such as fuel moisture, winds, rain and temperatures. These background factors will vary in the same way across the simulations with and without the prescribed burn program. The purpose of these initial simulations is to familiarize you with how the fire reacts to changing conditions.

Some of the tasks today will involve the use of these simulations. Please note that there is one house in this simulation of Ashley National Forest. The choices you will be asked to make refer to this house. You can see where it is placed in the forest in the top picture, and the bottom picture is a close-up. [In this appendix these pictures are shown on page xi]

The first two tasks involve betting on the outcomes of uncertain events. Usually we bet on events like sports or elections. Today you will be betting on events related to forest fires in our simulations.

You will be making bets with several betting houses or "bookies." This is similar to betting on a football game or a horse race.

To familiarize you with betting, we will first illustrate how it works with the example of a horse race.

Imagine a two-horse race between Blue Bird and White Heat. Several bookies offer different odds for the horses. The table below shows the odds offered by three bookies (A, B and C) along with the amounts they would pay if you bet $10 on the winning horse. At this point you should take some time to study the table.

Bookie	Stake	If you bet on Blue Bird and...		If you bet on White Heat and…	
		Blue Bird wins you get	White Heat wins you get	Blue Bird wins you get	White Heat wins you get
A	$10	$50	$0	$0	$12.50
B	$10	$33.33	$0	$0	$14.30
C	$10	$20	$0	$0	$20

For each bookie, whether you would choose to bet on Blue Bird or White Heat will depend on three things: your judgment about how likely it is that each horse will win, the odds offered by the bookie, and how much you like to gamble or take risks.

Betting on forest fires

Now that you are familiar with odds and betting, let us explain the forest fire betting task. You will be betting on two events. Recall the house that is located in the Ashley National Forest. You will be asked to bet on whether or not the house will burn in a simulated forest fire.

The first event is a forest fire that takes place in a year when the forest has not been managed through prescribed burns. In this case a lot of fuel is left in the forest, increasing the intensity and spread of fires. You will be asked to place a bet on whether or not the house will burn in the simulated fire. This will be Task 1.

The second event is a forest fire that takes place in a year when the forest has been managed through prescribed burns. A reduced fuel level reduces the intensity and spread of fires. Again, you will be asked to bet on whether or not the house will burn in the simulated fire. This will be Task 2.

For each event there will be 9 bookies offering odds. **You will make bets with all 9 bookies. For each event you are given a $5 stake to bet with**. If the number on the card in the envelope you picked at the beginning is either a 1 or a 2, you will be paid for the corresponding betting task. If so, we will also have to roll a die to choose one of these 9 betting houses. Thus, each of your bets is equally likely to be chosen to determine your earnings.

Before you place your bets you will get the chance to experience some fire simulations. In these simulations there will be variations in fire management and other background factors, such as weather. This will make it possible for you to assess how likely you think it is that the house will burn in the two events you are betting on.

After placing your bets we will run an additional simulation, which will be used to determine your earnings. Thus, depending on your bets and on whether the house burns or not in this final simulation, your earnings will be calculated.

What determines the risk of the house burning?

We have generated a number of fire simulations by varying several background factors that determine how severe a wild fire is.

The first background factor is the temperature and humidity. In one case we have a *high temperature and low humidity*, which makes for a more severe fire. In this case the morning low temperature is 60 degrees and the afternoon high is 99 degrees, with morning high humidity of 70% and afternoon low of 10%. And in another case we have a relatively *low temperature and high humidity*, which makes for a less severe fire. This time the morning low temperature is 40 and the afternoon high is 85, with morning high humidity of 90% and afternoon low of 60%.

The <u>second</u> background factor is the wind speed. This will be either *high or low*, corresponding to 5 miles per hour or 1 mile per hour. Wild fire spreads more rapidly when winds are high.

The <u>third</u> background factor is the fuel moisture in the vegetation. This will either be *high or low*, with expected effects on the severity of the wild fire. When fuel moisture is high the moisture content of all dead vegetation is set to 20%, and when it is low it is set to 3-5%. Further, when the dead fuel moisture is high the proportion of dead vegetation is low (0-10%), and when the dead fuel moisture is low the proportion of dead vegetation is higher (25-50%).

The <u>fourth</u> background factor is the duration of the fire, which will either be 1 day or 2 days. You can think of this as reflecting rainfall or fire-fighting activities. The longer a fire lasts, the more it will spread across the landscape.

The <u>final</u> background factor is the location of the initial lightning strike that ignites the fire. This could be in the center of Ashley National Forest, in the north (in the mountains), or in the south. Each is equally likely when we select a scenario to actually pay you. The house is in the center of Ashley, slightly to the east and close to the foothills.

In the initial series of simulations you will have a chance to understand the nature of the fires and how it depends on these background factors. You will experience forest fires under both benign and severe conditions.

For the final simulation which determines your earnings, the background factors will be determined using dice. We will roll the dice for each of the 5 background conditions: temperature/humidity (2 possibilities), wind (2 possibilities), fuel moisture/proportion of dead vegetation (2 possibilities), duration (2 possibilities), and, the location of the lightning strike that starts the fire (3 possibilities).

This table shows you how a roll of a standard 6-sided die will determine the background factor that we will use in the final simulation that determines our payments:

Die roll	**1-3**	**4-6**
Temperature	Low	High
Air humidity	High	Low

Die roll	**1-3**	**4-6**
Wind speed	Low	High

Die roll	**1-3**	**4-6**
Fuel Moisture	High	Low
Proportion Dead Fuel	Low	High

Die roll	**1-3**	**4-6**
Duration	1 day	2 days

Die roll	**1-2**	**3-4**	**5-6**
Lightning	North	South	Central

In addition, the simulation will be determined by whether the fuel load is high or low, depending on whether your betting task is number 1 (high fuel load) or 2 (low fuel load).

Before placing your bets you will experience four of these scenarios. For each of the high and low fuel load cases you will experience the most benign and the most intense combination of background factors

- <u>Benign</u>: Temperature low and air humidity high; wind speed low; fuel moisture high and proportion dead fuel low; duration 1 day; and lightning strike in the north.

- <u>Intense</u>: Temperature high and air humidity low; wind speed high; fuel moisture low and proportion dead fuel high; duration 2 days; and lighting strike in the central area.

Risks when fuel load is high

Here we will statistically describe the spread of wild fires generated by the simulation model and how it varies due to varying background factors. If we consider each of the possible background factors, not counting the variation in fuel load due to prescribed burning, there are 48 scenarios that are possible. Each scenario is a combination of temperature/humidity (high/low or low/high), wind (high or low), fuel moisture/proportion of dead vegetation (high/low or low/high), duration (short or long), and location of lightning striking (center, north, or south).

The graph below [In this Appendix the graph is included on page xii as Graph 1] shows you what happens when the prescribed burn is *not* undertaken, that the fuel load is high. The horizontal or bottom axis shows the total acreage of Ashley National Forest that burns, in percentages. So the most severe fires burn slightly more than 60% of the whole area (in the bottom right hand side of the graph). But many of the fires burn less than 10% of the whole area (in the bottom left hand side of the graph). The vertical axis shows the number of times that the fire burns each percent of the whole area. So we see that the fire burned between 0% and 2½% of the whole area in 11 of the 48 scenarios (the first bar at the bottom left) and over 60% of the area in 3 of the 48 scenarios (the last two bars).

Risks when fuel load is low

We can generate a similar graph, assuming the same background risk factors, in the event that the prescribed burn policy is implemented and the fuel load is low. [In this appendix this graph is shown on page xii as Graph 2].

The results are clear: lowering the fuel load by using the prescribed burn lowers the risk of having more severe wild fires. It does not eliminate those risks, but now almost every wild fire burns less than 5% of the whole area of Ashley National Forest. There are some wild fires that are more severe, even with prescribed burn policy in place.

You should also keep in mind that these displays refer to the percent of the whole area of Ashley National Forest that is burned. Even if it is only 1%, if that 1% happens to be the house, the house will burn. Of course, you can judge the risk of that for yourself.

Experiencing the risks

You will now be given a chance to experience the risks we have been describing before you place your bets. For each of the high and low fuel load cases you will experience the most benign and the most intense combination of background factors. So you will experience a total of four fire simulations.

- Benign conditions with no prescribed burn policy in place.
- Intense conditions with no prescribed burn policy in place.
- Benign conditions with a prescribed burn policy in place.
- Intense conditions with a prescribed burn policy in place.

	Simulation 1 No prescribed burn	**Simulation 2** No prescribed burn	**Simulation 3** Prescribed burn	**Simulation 4** Prescribed burn
Temperature/ Humidity	Low/High	High/Low	Low/High	High/Low
Wind Speed	Low	High	Low	High
Fuel moisture/ Proportion of dead vegetation	High/Low	Low/High	High/Low	Low/High
Duration	1 day	2 days	1 day	2 days
Lightning	North	South	North	South

Your bets for the first two tasks

Now you are ready to place your bets in the first two tasks as described earlier. You will be placing bets on two events:

1. For a simulation when the fuel load is high, because prescribed burning has not been used, you will bet on whether or not the house will burn.

2. For a simulation when the fuel load is low, because prescribed burning has been used, you will bet on whether or not the house will burn.

For each bet you will face odds from 9 bookies. Please place a bet for each of the bookies for each of the two events.

Later you will roll the die several times to randomly select the background factors for the final simulation which will determine your earnings.

Your payoff is determined by four things:

- whether the number on the card in the envelope is a 1 or a 2
- which bookie is chosen to be played out using a 10-sided die;
- what your bet is for the chosen bookie; and
- the outcome of the final simulation

Please look at the first decision sheet. It is called “Place a bet with each bookie when fuel load is high because prescribed burning has not been used.” The table has 5 columns. Columns 3 and 4, labeled “If you bet that the house will burn in a forest fire and it…” and “If you bet that the house will not burn in a forest fire and it…”, show you the dollar earnings you get from each bookie depending on whether the house burns or not in the final simulation. Each row in the table represents a different bookie. Recall that we will later roll a die to select only one of these bookies for payment, and only if the number on the card in the envelope has a number “1” on it representing this first task.

When you have finished filling in this first decision sheet, please continue with the second one called “Place a bet with each bookie when fuel load is low because prescribed burning has been used.”

Before we go on, do you have any questions?

Tasks 3 - 5: Pay for prescribed burn or not

Before we run the simulation you will be completing some more tasks. The next set of tasks also concern the question of whether the house burns or not in the simulated fire. The type of decision you make here is different from before, however. Again, if the numbered card in the envelope is a 3, or a 4, or a 5, then your earnings will be determined by the choice you make in one of these tasks.

You are asked to make a choice between paying for the prescribed burning of the forest or not. Before you make a choice you will be given an initial credit. This credit includes the value of “owning” the simulated house in the forest. In Task 3 the initial credit is $20 the house is valued at $8. In Task 4 the initial credit is $60 and the house is valued at $28. In Task 5 the initial credit is $80 and the house is valued at $38.

If you choose to pay for prescribed burn we will run a fire simulation that is based on the low fuel load. The background factors that determine the severity of the fire, such as weather conditions or the location of lightning strikes, will be determined by rolling dice. You will be asked to indicate how much you are willing to pay for the prescribed burn. This amount will be deducted from your initial credit. If the house does not burn in the simulation, you keep the remaining credit, but if it burns you lose the amount that the house is worth.

If you choose not to pay for prescribed burn we will instead run a fire simulation that is based on the high fuel load. If the house does not burn in the simulation, you therefore keep the entire credit, but if it burns you lose the amount that the house is worth.

In either case, recall that these choices will determine your earnings only if the card in the envelope has the number 3, 4 or 5 on it.

Please look at the decision sheet for this table. Each row shows you a different cost of implementing the prescribed burn. The amount of prescribed burn that results is the same, independent of the amount paid for prescribed burn. Look at decision 1 at the top of the table. It gives a choice between doing the prescribed burn and not doing the prescribed burn, when the cost of the prescribed burn is zero.

Now look at decision 2. In this row the cost of the prescribed burn in $2. Are you willing to pay $2 for prescribed burning? All the other decisions are similar, with the cost of prescribed burn increasing by $2 for each successive row. In the very last row the cost of the prescribed burn equals the value of the simulated house. In this sheet the cost of the prescribed burn in the last row is $8.

We ask you to indicate YES or NO for each of the amounts shown. If Task 3 is chosen, you will roll a 6-sided die to pick one of the rows for payment. If you get a 6 you roll again. If Task 4 or Task 5 is chosen, you will roll a 20-sided die to pick one of these rows for payment.

For each row please think about the following: if this row is selected using the dice, would you be willing to pay the amount indicated so as to run the simulation with the lower fuel load instead of the higher fuel load?

Therefore, your payoff is determined by four things:

- whether the number on the card in the envelope is a 3, 4 or 5;
- which row is chosen to be using the 20-sided die;
- whether you said "yes" or "no" on that row, and
- whether or not the house burns in the simulation (which will use a low fuel load if you said "yes" and a high fuel load if you said "no")

Please complete the decision sheets for tasks 3, 4 and 5 now, unless you have any questions.

Task 6: Lottery choices

In task 6 you will be making choices between pairs of lotteries. Please look at the decision sheet for this task. The table shows ten rows. Each row is a paired choice between "Option A" and "Option B." These options are both lotteries that will be played out. You will make a choice between these two options on each row and record these in the final column.

We will use two 10-sided dice to determine your payoffs. The numbers on the two dice are added to get a number between 0-99. We will use the number 0 to serve as 100. Look at decision 1 at the top of the table. It gives a choice between getting $24 for certain and getting $1 for certain. The die will not be needed for this option.

Now look at decision 2. Option A pays $26 if you get a number between 1 and 10, and it pays $24 if you get a number between11-100. Option B pays $50 if you get a number between 1-10, and it pays $1 if the number is between 11-100. The other decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase.

If the number 6 is inside the envelope you picked, you will roll a ten-sided die to select one of the ten rows. Your choice for that row, option A or B, will be played out with two ten-sided dies and the outcome will determine your earning.

Therefore, your payoff is determined by three things:

- which lottery pair is chosen to be played out using the 10-sided die;
- which lottery you selected, A or B, for the chosen lottery pair; and
- the outcome of that lottery when you roll the two 10-sided dice.

Task 7: Lottery choices

This task is similar to the task you just completed, except in this task there is a chance you will lose money. Before you make your choices you will be given a credit of $50 and any loss will be deducted from this money to determine your payment. You cannot lose more than $50.

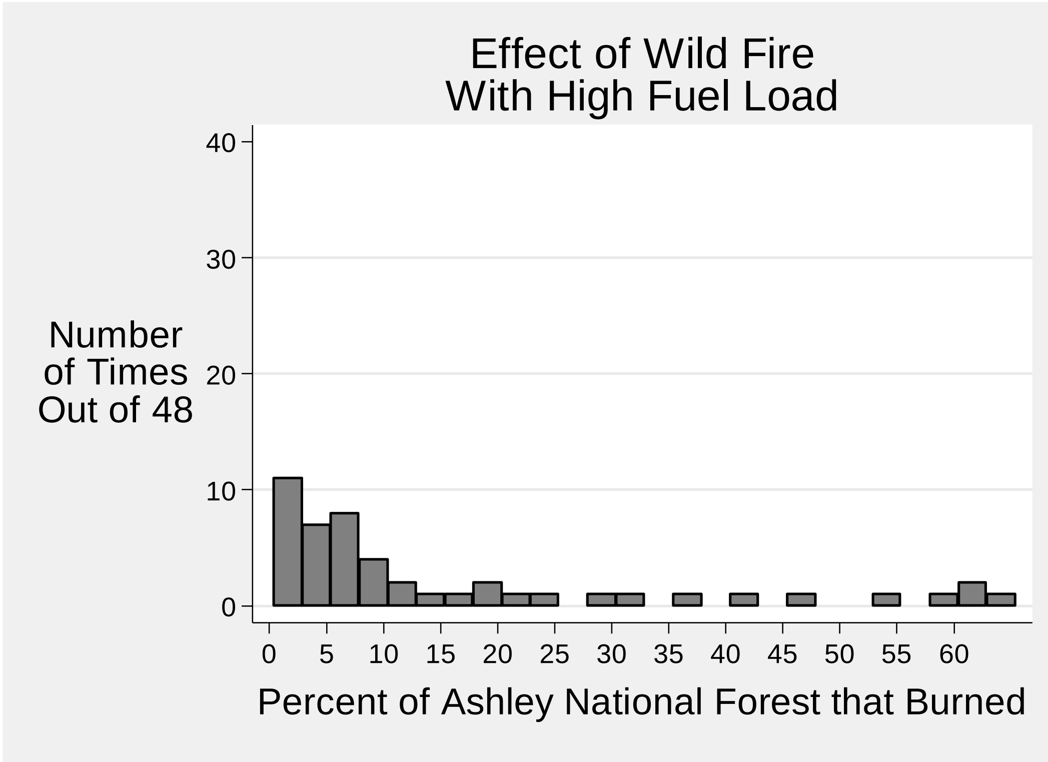
Please look at the decision sheet for Task 7. In this decision sheet you have a credit of $50. Option A in the first row gives -$26 for numbers 1-100. Since you have a credit of $50, playing this lottery will give you a final payoff of $50 - $26 = $24. Similarly, Option B in the first row will give you a payoff of $50 – $49 = $1.

Each lottery in Option A of Task 7 has the payoffs -$26 and -$24 except the first lottery, which gives -$26 for certain. Each lottery in Option B has the payoffs -$49 and -$0 except the first lottery, which gives -$49 for certain. The chances of getting these payoffs are different in each row. As you move down the table, the chances of losing the higher amounts decrease.

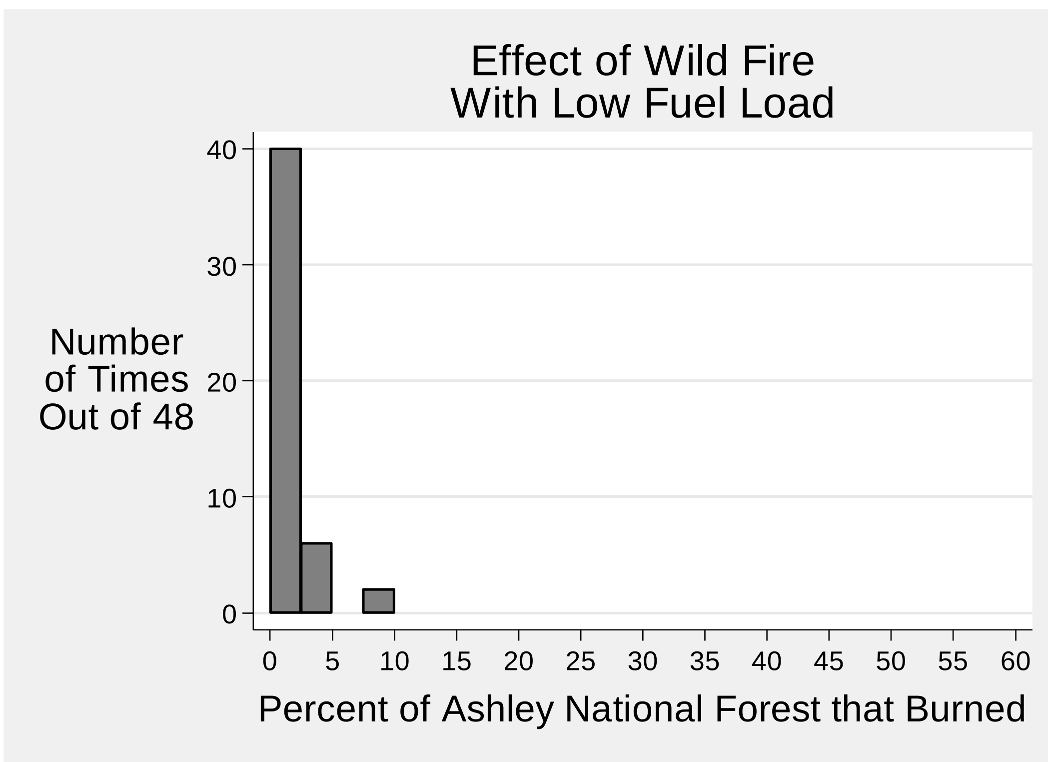

Forest Fire Demo
Load
N
W
E
S
Flying Mode *PAUSED*
P – play
Page Up – elevate
Page Down – descend
W, Up – move forward
S, Down – move backward
A, Left – strafe left
D, Right – strafe right
H – toggle interface
M – change to path designer mode
[0d:00h:00m:00s]
[0d:05h:14m:56s]
[0d:00h:00m:00s]


Forest Fire Demo
Load
N
W
E
S
Flying Mode *PAUSED*
P – play
Page Up – elevate
Page Down – descend
W, Up – move forward
S, Down – move backward
A, Left – strafe left
D, Right – strafe right
H – toggle interface
M – change to path designer mode
[0d:00h:00m:00s]
[0d:05h:14m:56s]
[0d:00h:00m:00s]

Graph 1



Graph 2



1. Place a bet with each bookie when
Fuel Load is High because prescribed burning has not been used.

Bookie	Your Stake	A. If you bet that the house will burn in a forest fire and it…	B. If you bet that the house will not burn in a forest fire and it…	Do you bet your stake on A or B? (Circle A or B)
1	$5	does you get $50 does not you get $0	does you get $0 does not you get $5.55	A B
2	$5	does you get $25 does not you get $0	does you get $0 does not you get $6.25	A B
3	$5	does you get $16.66 does not you get $0	does you get $0 does not you get $7.19	A B
4	$5	does you get $12.50 does not you get $0	does you get $0 does not you get $8.33	A B
5	$5	does you get $10 does not you get $0	does you get $0 does not you get $10	A B
6	$5	does you get $8.33 does not you get $0	does you get $0 does not you get $12.50	A B
7	$5	does you get $7.19 does not you get $0	does you get $0 does not you get $16.66	A B
8	$5	does you get $6.25 does not you get $0	does you get $0 does not you get $25	A B
9	$5	does you get $5.55 does not you get $0	does you get $0 does not you get $50	A B

2. Place a bet with each bookie when
Fuel Load is Low because prescribed burning has been used.

Bookie	Your Stake	A. If you bet that the house will burn in a forest fire and it…	B. If you bet that the house will not burn in a forest fire and it…	Do you bet your stake on A or B? (Circle A or B)
1	$5	does you get $50 does not you get $0	does you get $0 does not you get $5.55	A B
2	$5	does you get $25 does not you get $0	does you get $0 does not you get $6.25	A B
3	$5	does you get $16.66 does not you get $0	does you get $0 does not you get $7.19	A B
4	$5	does you get $12.50 does not you get $0	does you get $0 does not you get $8.33	A B
5	$5	does you get $10 does not you get $0	does you get $0 does not you get $10	A B
6	$5	does you get $8.33 does not you get $0	does you get $0 does not you get $12.50	A B
7	$5	does you get $7.19 does not you get $0	does you get $0 does not you get $16.66	A B
8	$5	does you get $6.25 does not you get $0	does you get $0 does not you get $25	A B
9	$5	does you get $5.55 does not you get $0	does you get $0 does not you get $50	A B

3. Choose Prescribed Burn or Not for each possible cost.
You have $20. Your house is valued at $8.

Cost	Yes, I choose prescribed burn.	No, I do not choose prescribed burn.
$0	Yes	No
$2	Yes	No
$4	Yes	No
$6	Yes	No
$8	Yes	No

4. Choose Prescribed Burn or Not for each possible cost.
You have $60. Your house is valued at $28.

Cost	Yes, I choose prescribed burn.	No, I do not choose prescribed burn.
$0	Yes	No
$2	Yes	No
$4	Yes	No
$6	Yes	No
$8	Yes	No
$10	Yes	No
$12	Yes	No
$14	Yes	No
$16	Yes	No
$18	Yes	No
$20	Yes	No
$22	Yes	No
$24	Yes	No
$26	Yes	No
$28	Yes	No

5. Choose Prescribed Burn or Not for each possible cost.
You have $80. Your house is valued at $38.

Cost	Yes, I choose prescribed burn.	No, I do not choose prescribed burn.
$0	Yes	No
$2	Yes	No
$4	Yes	No
$6	Yes	No
$8	Yes	No
$10	Yes	No
$12	Yes	No
$14	Yes	No
$16	Yes	No
$18	Yes	No
$20	Yes	No
$22	Yes	No
$24	Yes	No
$26	Yes	No
$28	Yes	No
$30	Yes	No
$32	Yes	No
$34	Yes	No
$36	Yes	No
$38	Yes	No

6. Choose between Option A and Option B

Decision	Option A	Option B	Your Choice (Circle A or B)
1	$24 if throw of die is 1-100	$1 if throw of die is 1-100	**A B**
2	$26 if throw of die is 1-10 $24 if throw of die is 11-100	$50 if throw of die is 1-10 $1 if throw of die is 11-100	**A B**
3	$26 if throw of die is 1-20 $24 if throw of die is 21-100	$50 if throw of die is 1-20 $1 if throw of die is 21-100	**A B**
4	$26 if throw of die is 1-30 $24 if throw of die is 31-100	$50 if throw of die is 1-30 $1 if throw of die is 31-100	**A B**
5	$26 if throw of die is 1-40 $24 if throw of die is 41-100	$50 if throw of die is 1-40 $1 if throw of die is 41-100	**A B**
6	$26 if throw of die is 1-50 $24 if throw of die is 51-100	$50 if throw of die is 1-50 $1 if throw of die is 51-100	**A B**
7	$26 if throw of die is 1-60 $24 if throw of die is 61-100	$50 if throw of die is 1-60 $1 if throw of die is 61-100	**A B**
8	$26 if throw of die is 1-70 $24 if throw of die is 71-100	$50 if throw of die is 1-70 $1 if throw of die is 71-100	**A B**
9	$26 if throw of die is 1-80 $24 if throw of die is 81-100	$50 if throw of die is 1-80 $1 if throw of die is 81-100	**A B**
10	$26 if throw of die is 1-90 $24 if throw of die is 91-100	$50 if throw of die is 1-90 $1 if throw of die is 91-100	**A B**

7. Choose between Option A and Option B (You have a $50 credit)

Decision	Option A	Option B	Your Choice (Circle A or B)
1	-$26 if throw of die is 1-100	-$49 if throw of die is 1-100	A B
2	-$24 if throw of die is 1-10 -$26 if throw of die is 11-100	-$0 if throw of die is 1-10 -$49 if throw of die is 11-100	A B
3	-$24 if throw of die is 1-20 -$26 if throw of die is 21-100	-$0 if throw of die is 1-20 -$49 if throw of die is 21-100	A B
4	-$24 if throw of die is 1-30 -$26 if throw of die is 31-100	-$0 if throw of die is 1-30 -$49 if throw of die is 31-100	A B
5	-$24 if throw of die is 1-40 -$26 if throw of die is 41-100	-$0 if throw of die is 1-40 -$49 if throw of die is 41-100	A B
6	-$24 if throw of die is 1-50 -$26 if throw of die is 51-100	-$0 if throw of die is 1-50 -$49 if throw of die is 51-100	A B
7	-$24 if throw of die is 1-60 -$26 if throw of die is 61-100	-$0 if throw of die is 1-60 -$49 if throw of die is 61-100	A B
8	-$24 if throw of die is 1-70 -$26 if throw of die is 71-100	-$0 if throw of die is 1-70 -$49 if throw of die is 71-100	A B
9	-$24 if throw of die is 1-80 -$26 if throw of die is 81-100	-$0 if throw of die is 1-80 -$49 if throw of die is 81-100	A B
10	-$24 if throw of die is 1-90 -$26 if throw of die is 91-100	-$0 if throw of die is 1-90 -$49 if throw of die is91-100	A B

8. Choose between Option A and Option B (You have a $20 credit)

Decision	Option A	Option B	Your Choice (Circle A or B)
1	-$8 if throw of die is 1-6 -$0 if throw of die is 7-100	-$8 if throw of die is 1-29 -$0 if throw of die is 30-100	**A B**
2	-$10 if throw of die is 1-6 -$2 if throw of die is 7-100	-$8 if throw of die is 1-29 -$0 if throw of die is 30-100	**A B**
3	-$12 if throw of die is 1-6 -$4 if throw of die is 7-100	-$8 if throw of die is 1-29 -$0 if throw of die is 30-100	**A B**
4	-$14 if throw of die is 1-6 -$6 if throw of die is 7-100	-$8 if throw of die is 1-29 -$0 if throw of die is 30-100	**A B**
5	-$16 if throw of die is 1-6 -$8 if throw of die is 7-100	-$8 if throw of die is 1-29 -$0 if throw of die is 30-100	**A B**

9. Choose between Option A and Option B (You have a $20 credit)

Decision	Option A	Option B	Your Choice (Circle A or B)
1	-$8 if throw of die is 1-6 -$0 if throw of die is 7-100	-$8 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
2	-$10 if throw of die is 1-6 -$2 if throw of die is 7-100	-$8 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
3	-$12 if throw of die is 1-6 -$4 if throw of die is 7-100	-$8 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
4	-$14 if throw of die is 1-6 -$6 if throw of die is 7-100	-$8 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
5	-$16 if throw of die is 1-6 -$8 if throw of die is 7-100	-$8 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**

10. Choose between Option A and Option B (You have a $80 credit)

Decision	Option A	Option B	Your Choice (Circle A or B)
1	-$38 if throw of die is 1-6 -$0 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
2	-$40 if throw of die is 1-6 -$2 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
3	-$42 if throw of die is 1-6 -$4 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
4	-$44 if throw of die is 1-6 -$6 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
5	-$46 if throw of die is 1-6 -$8 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
6	-$48 if throw of die is 1-6 -$10 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
7	-$50 if throw of die is 1-6 -$12 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
8	-$52 if throw of die is 1-6 -$14 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
9	-$54 if throw of die is 1-6 -$16 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
10	-$56 if throw of die is 1-6 -$18 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
11	-$58 if throw of die is 1-6 -$20 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
12	-$60 if throw of die is 1-6 -$22 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
13	-$62 if throw of die is 1-6 -$24 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
14	-$64 if throw of die is 1-6 -$26 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B
15	-$66 if throw of die is 1-6 -$28 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	A B

16	-$68 if throw of die is 1-6 -$30 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	**A** **B**
17	-$70 if throw of die is 1-6 -$32 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	**A** **B**
18	-$72 if throw of die is 1-6 -$34 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	**A** **B**
19	-$74 if throw of die is 1-6 -$36 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	**A** **B**
20	-$76 if throw of die is 1-6 -$38 if throw of die is 7-100	-$38 if throw of die is 1-29 -$0 if throw of die is 30-100	**A** **B**

11. Choose between Option A and Option B (You have a $80 credit)

Decision	Option A	Option B	Your Choice (Circle A or B)
1	-$38 if throw of die is 1-6 -$0 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
2	-$40 if throw of die is 1-6 -$2 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
3	-$42 if throw of die is 1-6 -$4 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
4	-$44 if throw of die is 1-6 -$6 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
5	-$46 if throw of die is 1-6 -$8 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
6	-$48 if throw of die is 1-6 -$10 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
7	-$50 if throw of die is 1-6 -$12 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
8	-$52 if throw of die is 1-6 -$14 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
9	-$54 if throw of die is 1-6 -$16 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
10	-$56 if throw of die is 1-6 -$18 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
11	-$58 if throw of die is 1-6 -$20 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
12	-$60 if throw of die is 1-6 -$22 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
13	-$62 if throw of die is 1-6 -$24 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
14	-$64 if throw of die is 1-6 -$26 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B
15	-$66 if throw of die is 1-6 -$28 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	A B

16	-$68 if throw of die is 1-6 -$30 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
17	-$70 if throw of die is 1-6 -$32 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
18	-$72 if throw of die is 1-6 -$34 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
19	-$74 if throw of die is 1-6 -$36 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**
20	-$76 if throw of die is 1-6 -$38 if throw of die is 7-100	-$38 if throw of die is 1-59 -$0 if throw of die is 60-100	**A** **B**